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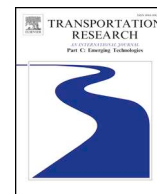
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# Electrifying urban ridesourcing fleets at no added cost through efficient use of charging infrastructure

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## ABSTRACT

Ridesourcing fleets present an opportunity for rapid uptake of battery electric vehicles (BEVs) but adoption has largely been limited to small pilot projects. Lack of charging infrastructure presents a major barrier to scaling up, but little public information exists on the infrastructure needed to support ridesourcing electrification. With data on ridesourcing trips for New York City and San Francisco, and using agent-based simulations of BEV fleets, we show that given a sparse network of three to four 50 kW chargers per square mile, BEVs can provide the same level of service as internal combustion engine vehicles (ICEVs) at lower cost. This suggests that the cost of charging infrastructure is not a significant barrier to ridesourcing electrification. With coordinated use of charging infrastructure across vehicles, we also find that fleet performance becomes robust to variation in battery range and placement of chargers. Our analysis suggests that mandates on ridesourcing such as the California Clean Miles Standard could achieve electrification without significantly increasing the cost of ridesourcing services.

## 1. Introduction

Meeting the Paris Climate Agreement's 2 °C and 1.5 °C targets will likely require massive deployment of electrified transportation (Schneider, 2017). Transportation represents the fastest-growing source of the world's greenhouse gas (GHG) emissions, with passenger cars accounting for close to a sixth of carbon dioxide emissions (Schneider, 2017), and car sales set to more than double by 2050 (Hao et al., 2016). In the U.S., transportation emissions have grown by over 20% since 1990, while emissions from almost all other sectors have decreased or remained constant (U.S. EPA, 2018). Battery electric vehicles (BEVs) could reduce transportation-related carbon emissions and urban air pollution (Hawkins et al., 2012; Cai and Xu, 2013) but despite years of strong public support, several barriers have slowed adoption of BEVs (Green et al., 2014; King et al., 2015). BEVs typically cost more than similar conventional and hybrid vehicles, and they provide a shorter driving range (Alternative Fuels Data Center, 2018a; Feng and Figliozzi, 2013). Charging infrastructure incurs additional cost, and the vast majority of public charging infrastructure consists of Level 2 chargers (Wood et al., 2017), which require several hours to fully recharge longer range BEVs. Public DC fast charging requires much less time (providing 60–80 miles of range in 20 min) (Alternative Fuels Data Center, 2018b), but relatively few fast-charging stations are available, and low utilization increases charging costs.

Ridesourcing—a taxi-like service that uses smartphone apps (from Uber, Lyft, etc.) to connect riders with self-employed drivers

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(Rayle et al., 2016)—holds potential to overcome these barriers and drive a step-change in transportation electrification. Vehicles used for ridesourcing accumulate mileage more quickly than vehicles used for personal purposes only, such that BEVs used for ridesourcing can provide greater benefits to vehicle owners due to lower costs per mile (Greenblatt and Saxena, 2015; Li and Fitzgerald, 2018), and they provide better returns on public electrification investments in terms of reduced carbon emissions and air pollution per vehicle (Bauer et al., 2018a). In addition, because ridesourcing vehicles are typically driven in urban cores, ridesourcing BEVs could increase public health benefits while exposing many consumers to the technology, which might increase private BEV sales (George and Zafar, 2018; Jenn et al., 2018). Although ridesourcing currently represents a relatively small share of all vehicle miles traveled, the sector has experienced explosive growth that shows no sign of slowing (Conway et al., 2018), with some forecasts expecting the global market to increase almost three-fold by 2030 (Burgstaller et al., 2017; Clewlow and Mishra, 2017), and others predicting that, with the advent of vehicle automation, ridesourcing will soon dominate the transportation market (Johnson and Walker, 2016).

Meanwhile, recent studies have shown that ridesourcing can increase both greenhouse gas emissions (Wenzel et al., 2019) and congestion (Erhardt et al., 2019). With local governments increasingly concerned about ridesourcing's adverse emissions impacts (Siddiqui, 2018), BEVs offer a potential solution. In California, the public utility commission is tasked with establishing targets for emissions reductions for ridesourcing companies (California State Legislature, 2018), Uber has announced that all its vehicles in London will be electric or hybrid by 2025 (Walker, 2018), and Lyft has set a goal of 1 billion autonomous electric rides per year by 2025 (Etherington, 2017).

Despite such ambitious plans, early efforts at ridesourcing electrification have experienced mixed results. In a London pilot project, Uber found that over 80% of BEV drivers lacked access to home charging, and insufficient public infrastructure prevented drivers from serving as many rides as they could with internal combustion engine vehicles (ICEVs) (George and Zafar, 2018). Elsewhere, ridesourcing BEV drivers have reported declining rides because their vehicles lacked sufficient charge as well as losing revenue owing to time spent charging and looking for charging stations (Hagman and Langbroek, 2018; Said, 2018). In a pilot in South Korea, BEV taxis provided a much lower benefit-to-cost ratio compared with natural-gas-powered taxis because of limited charging infrastructure and battery range (Baek et al., 2016). In China, electric taxi drivers exhibit significant range anxiety, driving relatively short distances between charging events (J. Yang et al., 2018). In Hong Kong, surveys with taxi drivers and owners revealed that both the location of chargers and charging time are two of the most important factors affecting perception of BEV adoption (W.H. Yang et al., 2018).

While it is thus evident that ridesourcing electrification will require convenient and inexpensive public fast-charging charging infrastructure, there is limited public information regarding optimal infrastructure design and BEV fleet operation. Wood et al. (2018) built an optimization model of a hypothetical ridesourcing fleet in Columbus, Ohio, based on GPS data from cell phones. However, these data did not distinguish ridesourcing trips from trips taken by other modes, and the authors assumed that all drivers have access to home charging, whereas ridesourcing electrification in major cities likely will depend on public charging as discussed above. Ke et al. (2019) developed an optimization model to study scheduling of charging sessions in an electric ridesourcing fleet but did not base their analysis on real-world data and did not incorporate spatial constraints in the model. Tu et al. (2019) analyzed current trajectories of ridesourcing vehicles in Beijing and found that ubiquitous Level 2 charging at all driver homes and dwell locations would be required to electrify 90% of the fleet, but the authors did not account for the possibility that BEVs could have different trajectories than ICEVs.

Several previous studies have employed agent-based modeling techniques to study taxi fleets, but most focus on self-driving cars, and few have modeled BEVs (Bösch et al., 2017; Fagnant et al., 2015; Fagnant and Kockelman, 2014). Of those that do consider BEVs, the charging relocation strategy is typically either absent or simplistic. Chen et al. (2016) and Loeb et al. (2018) only allowed vehicles to charge when they did not have enough range to serve a trip, while Bischoff and Maciejewski (2014) only allowed vehicles to charge when at taxi stands. Hu et al. (2018) studied the feasibility of electrifying Yellow Taxis in NYC, defining “feasibility” as able to serve 99% of the same trips as an ICEV. They found that only 7% of the fleet could be electrified with current charging infrastructure, and half of the fleet could be electrified by installing approximately 400 additional charging stations. However, the authors did not consider charging congestion or relocation times after charging. They also placed several restrictions on when the vehicles could charge, such as being within half a mile of the nearest station. Yang et al. (2017) simulated electrification of taxis in Beijing to determine optimal charging siting, but they assumed charging would only occur when the taxis currently had idle time, i.e., they did not allow for relocation to charging stations. Similarly, Jia et al. (2018) used this data to simulate trip chains of distance equal to electric taxis' assumed range (150 km), and used the end points of these chains to estimate optimal locations for charging stations.

This study builds on previous work by extending the agent-based model presented in Bauer et al. (2018a), which incorporates flexibility as to when drivers relocate to charge. Both Wood et al. (2018) and Hu et al. (2018) determined charging and trip assignment separately, leading to much less flexibility in the timing of charging than if the two are determined simultaneously. Also, most previous studies have only allowed vehicles to charge when battery range falls below a threshold, and they have required vehicles to remain charging until at full capacity (Bischoff and Maciejewski, 2015; Chen, 2015; Hu et al., 2018; Loeb et al., 2018). We hypothesize that flexibility both in terms of when to charge and the extent of charge may be even more important for ridesourcing than for other BEV applications, because the vehicles return to the drivers' homes at the end of shifts, where charging stations may not be available. This hypothesis is consistent with Keskin and Çatay (2016), who found that allowing partial-charge sessions improves electric fleet performance.

In this study, we use data on ridesourcing trips and vehicle supply in San Francisco (SF) and New York City (NYC) to test the feasibility of meeting demand with supply given a variety of different input values, including for battery range and charging infrastructure. We show that (1) modest additions of public fast-charging infrastructure make urban ridesourcing electrification

practical under a range of vehicle battery capacities and operating strategies, and (2) the current economics of urban ridesourcing can support vehicle electrification and the required charging infrastructure at total costs lower than the costs of the ICEV-based ridesourcing system. In addition, the increased utilization of charging infrastructure due to ridesourcing BEVs could reduce public charging costs for all BEV users and further support large-scale transportation electrification. Therefore, electrifying the urban ridesourcing sector could be a cost-effective approach to reducing transportation-related greenhouse gas emissions and urban air pollution, and properly designed policies could realize these benefits with little or no cost burdens to governments, transportation network companies, or ridesourcing drivers.

The paper will proceed as follows. In Section 2, we use fleet-wide average statistics to motivate our hypothesis that BEVs employed in ridesourcing fleets have sufficient time to charge, and that given reasonable levels of charger utilization, infrastructure cost becomes affordable. In Section 3, we present the methods used to conduct agent-based simulations to verify this hypothesis, results of which are presented in Section 4. In Section 5, we conclude with policy implications and directions for future research.

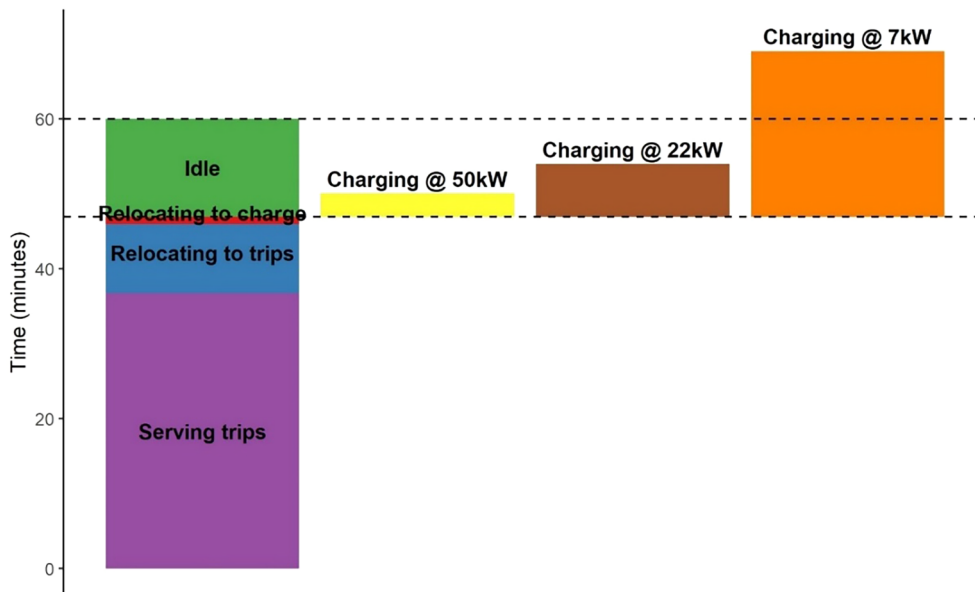
## 2. Theory

Contrary to common perception, simple economic reasoning suggests that ridesourcing drivers have adequate time to charge during their shifts, and that—given sufficient utilization—fast-charging infrastructure could pay for itself. As previous studies have noted (Parrott and Reich, 2018), the short rider wait times that are key to ridesourcing's value proposition are predicated on having a significant number of drivers waiting for ride requests at any given time. This idle time represents time when drivers could charge BEVs without losing revenue. As shown in Equation (1), the amount of idle time for drivers ( $t_{idle}$ ) can be expressed as a relation between driver wage rate ( $w$ ), the ratio of empty miles to passenger miles (deadheading ratio,  $r$ ) and the rate that could be earned by serving trips continuously ( $f$ ) multiplied by the time period ( $t_{tot}$ ), minus average refueling time ( $t_{fuel}$ ).

$$t_{idle} = t_{tot} * (1 - w/f * (1 + r)) - t_{fuel} \quad (1)$$

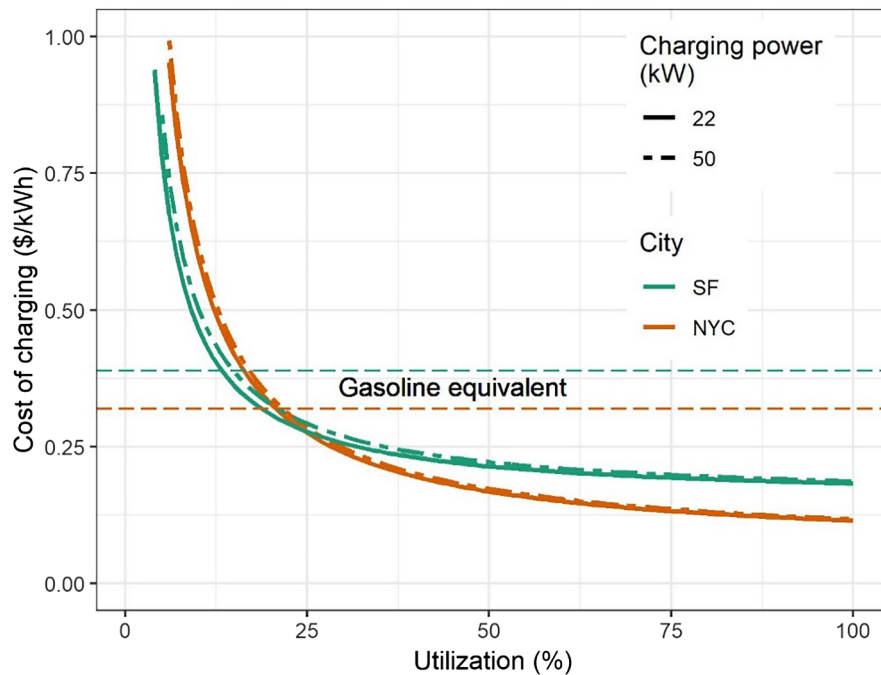
For instance, in NYC, a Uber riders' fare is determined as the sum of a fixed \$2.55 per trip base charge, a \$1.75 per mile charge and \$0.35 per minute charge, with 75% of this total accruing to the driver and the remaining 25% to Uber (Uber, 2018). Given an average speed of roughly 12 miles per hour and an average trip distance of 3 miles (City, 2015), a driver carrying passengers for a full hour would serve 4 trips, earning \$39.15 ( $f$ ). Assuming gross driver earnings ( $w$ ) average \$24 per hour (Hall and Krueger, 2018; Parrott and Reich, 2018), and a deadheading ratio (empty miles divided by passenger miles) of 0.25 (San Francisco County Transportation Authority, 2017), we can estimate that drivers in NYC are moving for roughly 46 min out of the hour, and have roughly 14 min in which to recharge the 9.2 miles they traveled. As shown in Fig. 1, a 50-kW charger can provide this amount of charge in roughly 3 min, suggesting that drivers have more than enough time to charge during their shift. Based on these assumptions, the average driver would have to charge less than once per shift, such that time spent relocating to charge is negligible.

On the other hand, data suggests that, in the U.S., public charging infrastructure is utilized less than 10% of the time (Francfort et al., 2015; Wolbertus et al., 2016), which often makes DC fast charging more expensive than gasoline on a per-mile-driven basis. As



**Fig. 1.** Distribution of time spent by an average NYC ridesourcing driver, with time cost of charging for both DC fast charging (50 kW) and Level 2 charging (22 kW or 7 kW). We assume a vehicle energy consumption of 0.28 kWh/mile, equivalent to the performance of the 2018 Chevrolet Bolt (U.S. Department of Energy and U.S. EPA, 2018). For relocating to charge, we assume one charging session per 8-hour shift and an average relocation distance of 2.5 miles at a speed of 10 miles/h.





**Fig. 2.** Relationship between the total cost of charging infrastructure (capital cost, electricity, and demand charges) and percent utilization by time. Cost assumptions are shown in Table 2 in the methods section. Note that the curves for 50 kW and 22 kW chargers appear roughly the same because capital costs scale roughly linearly with the power rating.

shown in Fig. 2, once utilization surpasses about 15% (roughly 3.5 h per day), the combined cost of infrastructure and electricity becomes less than the equivalent cost of gasoline in both NYC and San Francisco (SF), and operational savings start to accrue. This suggests that the cost of charging infrastructure is highly sensitive to utilization.

These calculations suggest that neither the time required to charge nor the cost of infrastructure should pose significant barriers to ridesourcing electrification. This conclusion is based on several major assumptions: that charging in between trips does not affect the ability to serve demand for rides, that time spent relocating to charge is not significant, and that charger utilization greater than 3.5 h per day is feasible when accounting for relocation time and queuing at stations.

### 3. Methods

To test the assumptions listed above, we develop an agent-based model that routes a fixed number of active vehicles to trips, rebalances idle vehicles to match demand, and determines the best times for vehicles to charge given a fixed number of charging points and locations. We repeat this analysis numerous times for different combinations of the fixed input parameters (see Table 3) to determine the minimum charging infrastructure required for BEVs to generate at least as much revenue per shift-hour as ICEVs. We conduct this analysis with data for ridesourcing trips in both SF and NYC, integrated with data on travel times and distances from cell phones and GPS devices, along with driver characteristic data from government records and existing surveys.

#### 3.1. Fleet modeling

To route vehicles to trips and charging, we use an agent-based model originally described in Bauer et al. (2018a). Fig. 3 shows a flow-chart of the model process; an animation visualizing the simulation can be viewed on Youtube (Bauer et al., 2018b). Basically, the model heuristically relocates vehicles between trips to better serve demand and charge opportunistically. Proceeding chronologically, the model assigns each trip to the closest available vehicle that would have at least enough range to serve the trip, make it to the closest charging station, and commute home. Other studies have found that such an approach to trip assignment is equivalent to more optimal algorithms when there are enough idle vehicles (Hyland and Mahmassani, 2018). When more than one vehicle meets these criteria, the model assigns the one with the least earnings per hour to decrease disparity in earnings between drivers. If no vehicle can serve a trip within 10 min, it is allowed to be served by an idle vehicle that could have arrived at the pick-up point within 10 min of the request time, assuming it anticipated the demand and started driving in that direction immediately after its last drop-off. This “clairvoyant” approach was verified to be realistic in previous work through sensitivity analysis. We also ran simulations in which vehicles do not relocate in between trips, which support our main results (see Appendix C). In practice, there is no way to guarantee that all trips will be served within 10 min of the request time; we merely use this threshold as a basis for comparison between simulations.

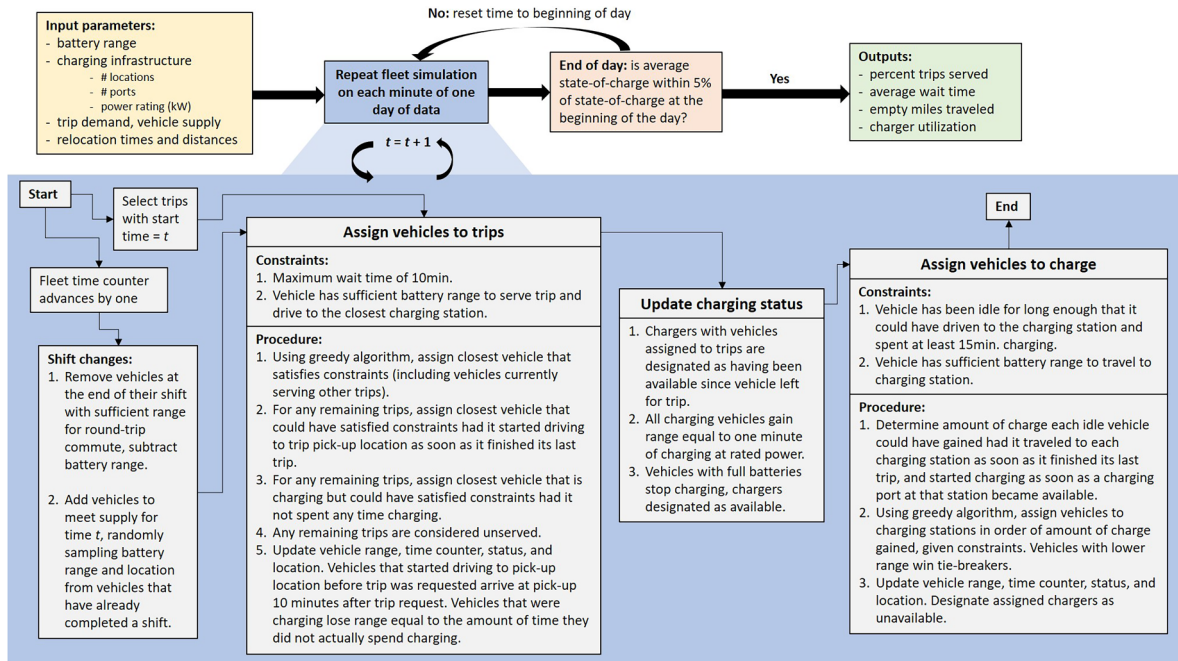


Fig. 3. Flow chart depicting agent-based simulation for BEV fleet operations.

If a trip request is not served within 15 min, it disappears and its revenue is lost. This constraint results in less than 4% lost revenue for ICEV fleets in NYC, and no lost revenue for ICEV fleets in SF. After trip assignment, idle vehicles are routed to charging stations using the following heuristic approach. Vehicles only relocate if they have been idle for enough time that they could have made it to the charging station, regained any charge lost in transit, and spent at least 15 additional minutes charging. Charging time is also limited by the amount of time chargers have been available, and occupied chargers are not available to accept vehicles. Assignments are made in order of the amount of energy gained. To test the impact of this routing algorithm, we conducted simulations with restrictions on charging (Table 3). The fixed charger locations are predetermined using k-means clustering of trip origins and destinations, which resulted in equivalent performance to the charger location algorithm described in Bauer et al. (2018a). This result is consistent with He et al. (2016), who found a similar clustering algorithm to be superior to other siting algorithms. In simulations with a fixed number of charging locations, placement of both the locations and chargers were determined with k-means clustering, and then each charger was moved to the nearest location.

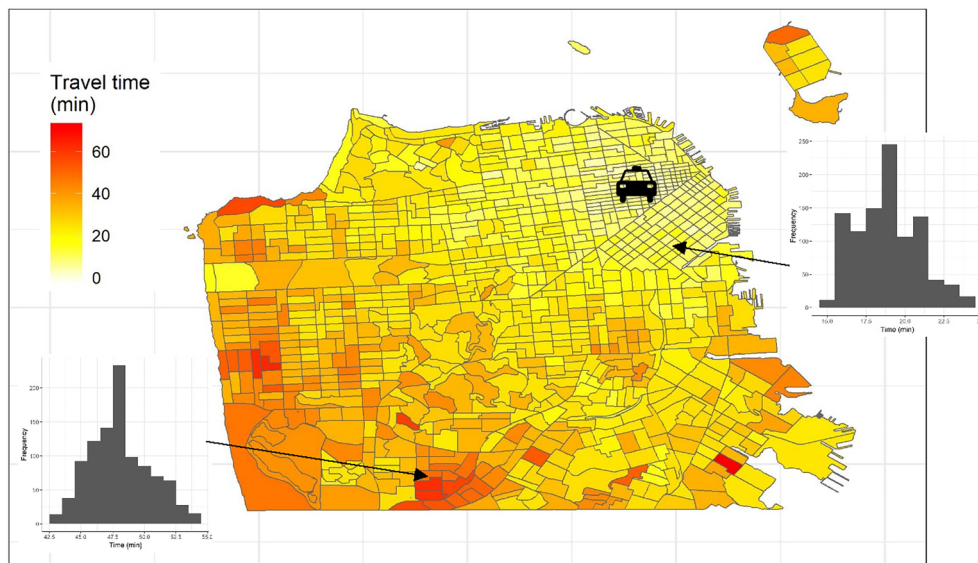
The main difference between the model developed for this study and that reported previously is that, at each minute, vehicles in the present study were removed or added to the fleet to match the time-varying fleet size determined exogenously. Each vehicle was assigned a shift length and commute distance (to and from home) randomly selected from a distribution based on survey data (see below for details). At the end of the shift, after serving any active trip, vehicles were designated as inactive as soon as they had enough range for their commute. When starting a new shift, initial vehicle range was selected randomly from the ranges of vehicles already to have completed their shifts, and the simulation repeated on the same 24-hour period until the average range of all vehicles (both active and inactive) at the end of the day was within 5% of what it was at the beginning of the day. Model inputs and outputs can be summarized as follows (see Table 3 for details):

Inputs: battery range, charging speed, number of chargers, number of charging locations, number of active vehicles by minute, driver shift length, driver commute distance, vehicle routing algorithms

Outputs: wait time by trip, revenue per shift-hour by vehicle, utilization by charger, deadheading distance and time by vehicle

### 3.2. Trip data

We conducted fleet simulations in both SF and NYC. To estimate trip data for NYC, we obtained data from the NYC Taxi and Limousine Commission (TLC) on trips taken by Yellow Taxis, Green Taxis, and For-Hire Vehicles (FHV), the latter of which includes all ridesourcing vehicles. The taxi datasets included geolocations and timestamps for trip pick-up and drop-off points, as well as trip distance, whereas the FHV dataset included only the number of trips by pickup zone and hour. To estimate individual trip records, we sampled trips from the combined taxi dataset to create a trip record with the same distribution by hour and pickup zone as the FHV data from February 2017, with 422,000 trips (the average for a weekday). This method accounts for the fact that FHVs tend to serve different neighborhoods, but it assumes that trips within each neighborhood are similar to taxi trips, which introduces a potential source of error. Pick-up and drop-off coordinates were clustered into cells with radius 250 m such that the maximum difference in



**Fig. 4.** Maps showing average travel times between a vehicle in downtown SF (depicted by the taxi icon) and every other TAZ in SF. Distributions of travel times to selected TAZ's are shown in inset histograms; these distributions are derived from GPS data provided by StreetLight Data. Note that distributions appear discontinuous due to rounding; the distributions they are drawn from are discrete but relatively smooth.

travel time would be 1 min assuming an average speed of 15 miles per hour. This clustering resulted in 6,500 total cells. Origin-destination matrices with times and distances between each of these cells were estimated using data downloaded from Google Maps API, as described in [Bauer et al. \(2018a\)](#).

The SF simulations are based on data obtained from the San Francisco County Transportation Authority (SFCTA) for Uber and Lyft trips starting and ending within city limits in November and December 2016. The data were aggregated by hour and traffic analysis zone (TAZ), and pickup minutes were estimated using LOESS regression, with the number of trips in each minute adjusted such that the total number of trips in each hour was equal to that in the original data. To estimate times and distances for each trip, we integrated the SFCTA data with data obtained from StreetLight Data Inc. based on GPS data from smartphone apps and in-vehicle devices. These data include the distribution of times and distances for vehicle trips taken between TAZ pairs by hour. While this GPS data is primarily sourced from personal vehicles, we assume that ridesourcing trips will have similar distance and time to trips made by personal vehicles between the same two points. StreetLight Data metrics were also used to create relocation matrices between each zone pair, similar to the data from Google described above. As shown in [Fig. 4](#), for each unique vehicle-trip and vehicle-charger pair, relocation times and distances are drawn randomly from the corresponding distribution provided by the data. Descriptive statistics for each city are shown in [Table 1](#).

### 3.2.1. Driver commutes and shift lengths

In both cities, we used survey data of Uber drivers ([Hall and Krueger, 2018](#)) and NYC TLC data on ridesourcing driver working hours ([Parrott and Reich, 2018](#)) to estimate the distribution of shift lengths for drivers. To estimate commute distances, in SF we obtained data on the home cities of about 1000 Uber/Lyft drivers within the Bay Area ([San Francisco Treasurer & Tax Collector's Office, 2018](#)), and we used the Google Maps distance from each city to SF to create a sampling distribution. Drivers originating outside the Bay Area were excluded, because we assumed they would have to charge somewhere in the Bay Area on their way to and from home, such that these “super-commuters” would not affect charging infrastructure requirements. Based on the distribution for

**Table 1**  
Summary of city characteristics.

Parameter	San Francisco	New York City
Area (square miles)	47	303
Number of trips	162,707	422,652
Average trip distance (miles) and duration (minutes)	2.7 miles 14 min	3.1 miles 15 min
Total number of active drivers	14,735	27,275
Average commute distance (miles)	12.4	10.0
Average shift length (hours)	4.6	7.0
Average driver earnings (\$/shift-hour)	18.55	24
Sources	San Francisco County Transit Authority; San Francisco Tax Collector's Office	NYC Taxi & Limousine Commission; <a href="#">Hall and Krueger (2018)</a> , <a href="#">Parrott and Reich (2018)</a>

**Table 2**  
Cost model components.

Component	Value	Source
Vehicle purchase	BEV 238: \$29,120 (2019 Chevrolet Bolt after federal tax credit; assumed that battery lasts at least as long as vehicle) ICEV: \$23,845 (2019 Toyota Camry)	Kelley Blue Book Co. (2018)
Vehicle lifetime	200,000 miles	NYC Taxi & Limousine Commission (2009)
Vehicle maintenance	BEV: \$0.04/mile ICEV: \$0.06/mile	Propfe et al. (2012)
Charger installation	7 kW: \$5,000 22 kW: \$20,000 50 kW: \$50,000	Agenbroad (2014), Union of Concerned Scientists (2017)
Electrical connection	Same cost as two additional chargers per location (includes cost of transformer upgrades)	Agenbroad (2014), Union of Concerned Scientists (2017)
Vehicle insurance	\$150/vehicle-month	Nerdwallet (2018)
Energy costs	BEV NYC: \$0.061/kWh + \$30.90/kW SF: \$0.151/kWh + \$15.90/kW (per-kW fees represent demand charges on peak power usage) ICEV NYC: \$0.09/mile (\$2.68/gallon, 30 miles/gallon) SF: \$0.11/mile (\$3.27/gallon, 30 miles/gallon)	conEdison (2018), Consolidated Edison Company of New York (2018), Energy Information Agency (2018), Pacific Gas and Electric Company (2015) Gasoline prices reflect 5-year averages

SF, in NYC we estimated commute distances by sampling from a gamma distribution with a scale factor of 2 miles and shape factor of 5 miles.

### 3.2.2. Number of drivers active

In SF, we obtained data from SFCTA on the average number of drivers active in each hour, then used LOESS regression to estimate the number active in each minute. In NYC, we calculated the total amount of revenue generated in each minute based on Uber fares (Uber, 2018), and we used this to determine the number of drivers that would be active if the average gross earnings were \$23/h, the average of values found in surveys (Hall and Krueger, 2018; Parrott and Reich, 2018). We then used LOESS regression to create a smooth curve for number of active drivers, adjusted such that the average earnings over the entire day were equal to \$23/h.

### 3.3. Cost analysis

Each component used to estimate the average cost per mile of each scenario is described in Table 2. The energy costs used are standard rates for small commercial entities, corresponding to the power range of charging stations considered. This does not include overhead expenses for a charging operator, assuming stations may be either publicly-owned or managed by the ridesourcing companies themselves. All amortization calculations assume an annual discount rate of 5%, a value commonly used to evaluate the cost of long-term projects (IWGSCG, 2016). We ran a cost sensitivity using a 10% rate (roughly the long-term average stock market return, see MoneyChimp, 2018), but found that results for the difference in net revenue between ICEVs and BEVs changed by only -\$0.07 to +\$0.04 per shift-hour, which is a very small percentage of total revenue.

### 3.4. Simulation runs

As shown in Table 3, we conducted simulations for a variety of scenarios for vehicle range, charging infrastructure, and charging relocation strategy (i.e. the rules that determine when vehicles go to charge), for a total of 360 BEV fleet simulations (180 for each city). We also conducted an ICEV fleet simulation in each city for comparison. We then determined whether each BEV fleet provided equivalent service to the ICEV fleet, defined as earning at least 95% as much revenue per hour, with no more than 5% additional empty miles and average wait times no more than 1 min longer.

## 4. Results & discussion

### 4.1. Feasibility of ridesourcing electrification by scenario

As shown in Fig. 5, our simulation results suggest that BEVs with 238 miles of range (equivalent to the Chevrolet Bolt EV) can provide equivalent service to ICEVs in a range of different infrastructure scenarios in both cities (see Appendix B for full results). However, the ability of the fleet to serve demand is sensitive to both charging speed and charging relocation strategy. Using chargers rated at 7 kW—the most common form of public infrastructure today—does not allow for equivalent service in any of our simulations, suggesting that such slow charging is not sufficient for ridesourcing electrification. This result is consistent with the analysis

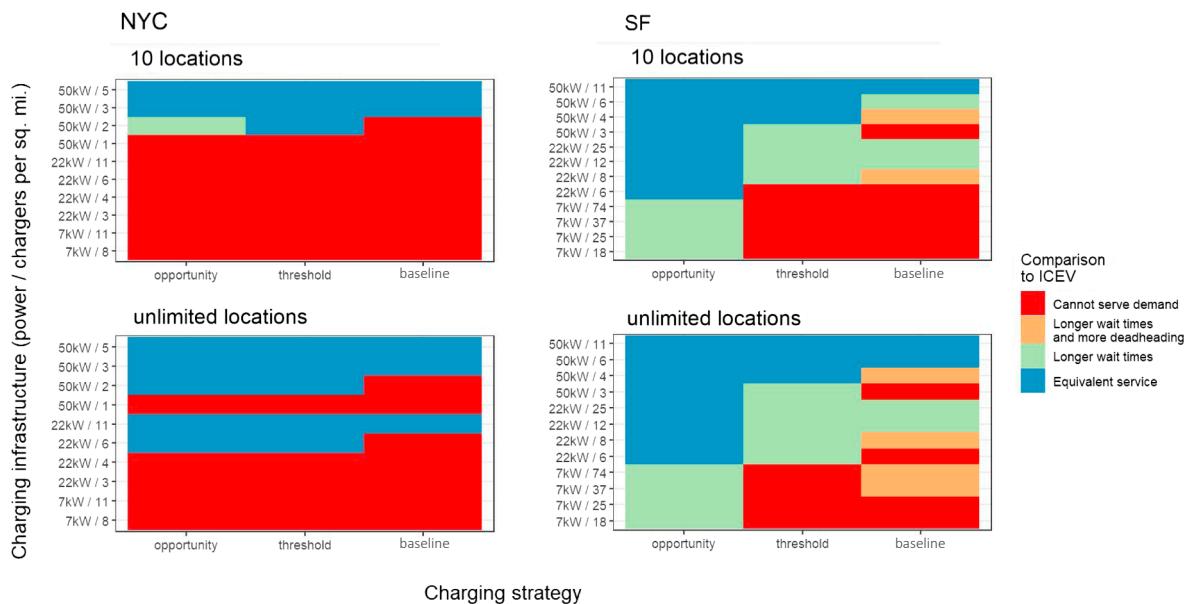
**Table 3**  
Description of simulation runs.

Parameter	Values simulated
Battery range	90 miles (based on 2019 Nissan LEAF with decreased range from winter driving or capacity fade), 238 miles (based on 2019 Chevy Bolt advertised range)
Charger utilization	25%, 50%, 75%, 100%
Charging speed	7.7 kW (present-day Level 2 charging), 22 kW (next-generation Level 2 charging), <a href="#">Qualcomm (2017)</a> 50 kW (public DC fast charging)
Number of chargers	Total distance * 1.4 / (Charging rate per hour * 24 h * charger utilization)
Number of charging locations	Unrestricted, 10 locations
Charger distribution strategy	k-means clustering (“optimal”), random point selection after k-means clustering to 5000 points (“random”), random point selection from bottom 20% of points by total number of trips within a 1.5-mile radius (“perimeter”) (tested only with 50% charger utilization and 50-kW charging)
Charging relocation strategy	Optimal routing (“opportunity”), optimal when < 20% state of charge (SOC) (“threshold”), move to closest available charger when < 20% SOC (“baseline”)

summarized in Fig. 1. Using 22-kW charging works in the “opportunity” relocation scenario in SF and when the number of locations is unrestricted in NYC, while using 50-kW charging (DC fast charging) allows BEVs to provide equivalent service across a wide range of scenarios. This result suggests that DC fast charging infrastructure rated at 50 kW is both necessary and sufficient for ridesourcing electrification.

In the “baseline” scenario, in which drivers have no information on when they should charge and only have information on which chargers are available when they start moving there, only 50-kW charging allows for equivalent service in both cities. This scenario represents how BEVs currently operate, suggesting that 50 kW charging will be necessary to initiate BEV penetration. In NYC, 22-kW charging can provide equivalent service if there is no restriction on the number of charging locations, but when BEV penetration is low, there will not be enough utilization to support more than a few locations. On the other hand, the fact that 22-kW charging works in many cases suggests that 50-kW charging may work even if our model is too optimistic, and effective charging speed is lower in practice when accounting for time spent parking and plugging in.

If fleet operators are able to direct vehicles to charge only when they have enough idle time to do so (“opportunity” and “threshold” scenarios), the number of 50-kW chargers required decreases to two per square mile in NYC (512 total chargers), and three per square mile in SF (175 total chargers). In the “threshold” scenario, vehicles are only available to charge once their battery range falls below 20%, whereas in the “opportunity” scenario, vehicles are available to charge whenever idle. The former scenario



**Fig. 5.** Results for all simulations, showing the performance of a fleet of BEVs with 238-mi. range relative to a fleet of ICEVs for each combination of charging infrastructure, battery range and charging relocation strategy. “Opportunity” represents simulations where vehicles are routed to charge whenever they have enough idle time to make it worthwhile, “threshold” represents simulations where vehicles are only allowed to charge when below 20% state of charge, and “baseline” means that as soon as vehicles reach 20% state of charge, they move to the closest available charger whether or not they have enough time to gain a meaningful amount of charge, and whether or not there is another vehicle moving to the same charger. Ten was chosen as the number of charging locations for the restricted-location scenarios because this was considered a lower bound on the number of charging sites that could be feasibly deployed in a city.



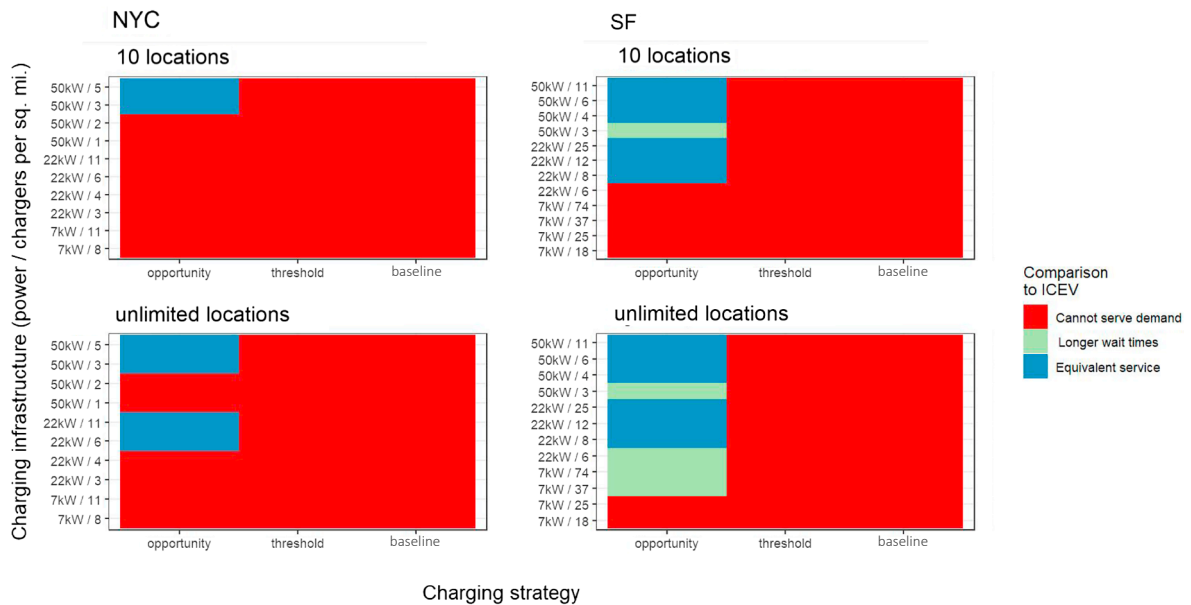


Fig. 6. Results for all simulations with 90-mi. battery range. Labels are the same as in Fig. 5.

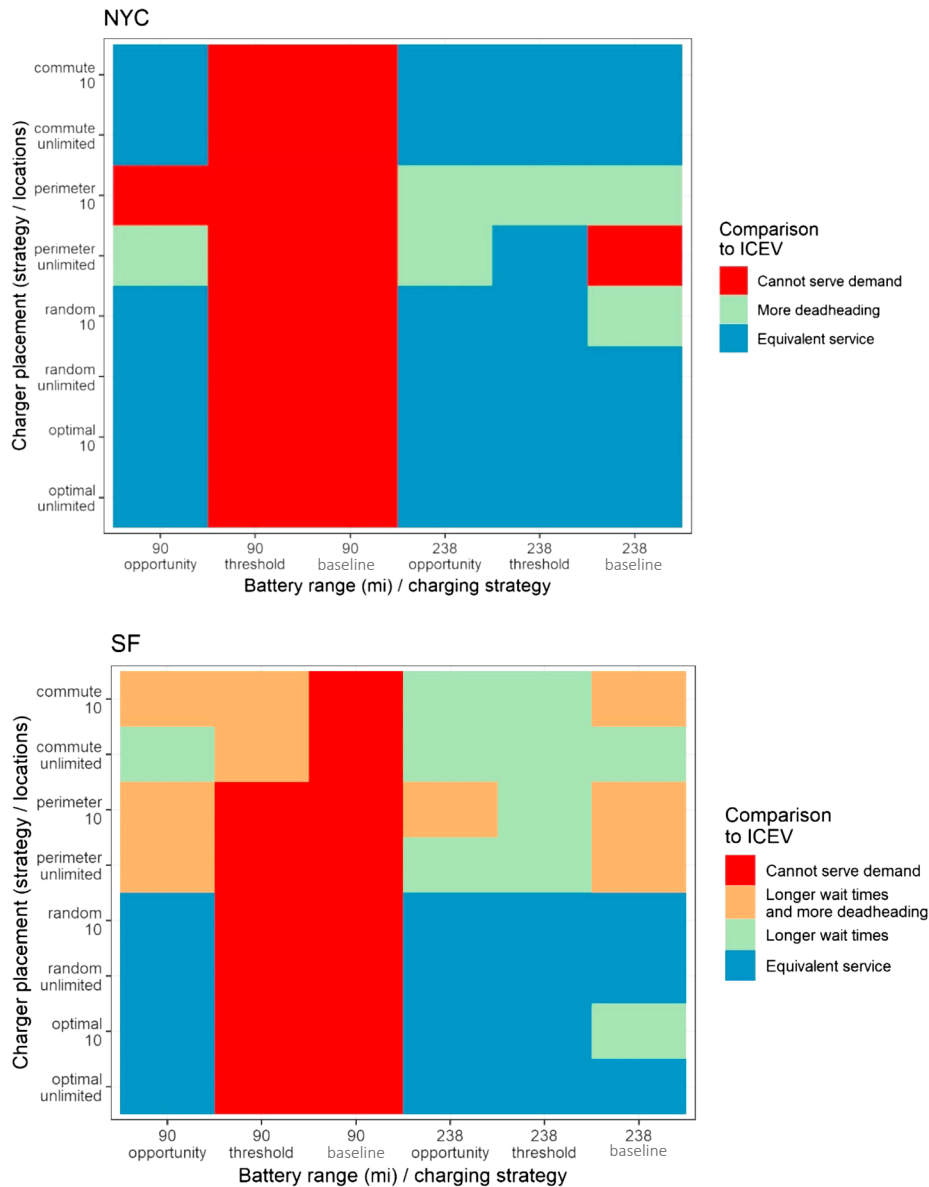
performs slightly better in NYC, while the latter performs better in SF, likely because the larger area or greater congestion of NYC induces a larger penalty for charging frequently. This result suggests that some form of scheduling system for charging stations can greatly improve electric vehicle reliability, which is consistent with findings from previous studies (Conway, 2017; Z. Dong et al., 2018; Tian et al., 2016).

In some ways, 238-mi. range represents an ideal case; to account for the impact of colder temperatures, more aggressive driving, using vehicles with less battery range, and capacity fade over time, we also ran each simulation with 90 miles of battery range. As shown in Fig. 6, such vehicles can also provide equivalent service to ICEVs in both cities with 50-kW charging so long as timing of charging is managed efficiently (“opportunity” scenario), suggesting that such a capability makes fleet performance insensitive to battery range. In turn, using vehicles with less range could decrease operating costs by reducing vehicles’ up-front costs and extending batteries’ functional lifetime.

As shown in Fig. 7, fleet performance is also relatively robust to how the chargers are sited. Relative to clustering chargers by trip origins and destinations (“optimal” scenario using k-means clustering), results remain largely unchanged when chargers are placed semi-randomly (“random” scenario, i.e. selecting locations randomly after using k-means clustering to narrow down selection to 5000 points), suggesting that mildly perturbing placement does not affect fleet performance. Even if chargers are placed only on the periphery (“perimeter” scenario, randomly selecting points from areas with low trip density), revenue remains stable in both cities, and in NYC overall service with the “threshold” charging relocation strategy remains comparable to the ICEV fleet. If this scenario is modified such that charging at the beginning and end of shifts is incorporated into drivers’ commutes (“commute” scenarios), fleet performance in NYC becomes equivalent to the “optimal” charger placement scenario. Average wait time remains roughly 3 min longer in SF, but this may be because the trip data does not include trips entering or leaving city limits. This result suggests that in some cases, if many ridesourcing drivers come from outside the city (e.g. over half in SF) (San Francisco Treasurer & Tax Collector’s Office, 2018), placing charging near popular commute routes may be sufficient. In summary, it appears that charging placement has relatively little impact as compared to coordinated charging management, as the latter enables the use of short-range BEVs. A map of each charging distribution is shown in Fig. 8.

#### 4.2. Total costs of ridesourcing electrification

The results presented above suggest that ridesourcing fleets can provide high levels of charger utilization. In both cities, fleets with average charger utilization of over 12 h per day were feasible with both 22-kW and 50-kW charging. With 50-kW charging and some management of charging timing (“opportunity” and “threshold” scenarios), fleets in both cities achieved charging utilization of up to 20 h per day while providing equivalent service to ICEVs. These results correspond to about 750 50-kW chargers in NYC, and 175 in SF, with densities of about three chargers per square mile in both cities (NYC covers an area roughly five times as large as SF). These quantities are roughly equivalent to the total number of gasoline pumps in each city (Google, 2018). In comparison, NYC currently only has 16 public fast chargers, but it plans to build up to 1000 more by 2020 (NYC City Hall, 2017). SF currently has 20 fast chargers spread across 13 locations (PlugShare, 2018), but there is public funding for the installation of several thousand additional chargers (power ratings have not been publicly announced) (Avalos, 2018; Electric Vehicle Grant Programs, 2018). Based on our results, these existing plans are more than sufficient to fully electrify ridesourcing in these cities provided that chargers are



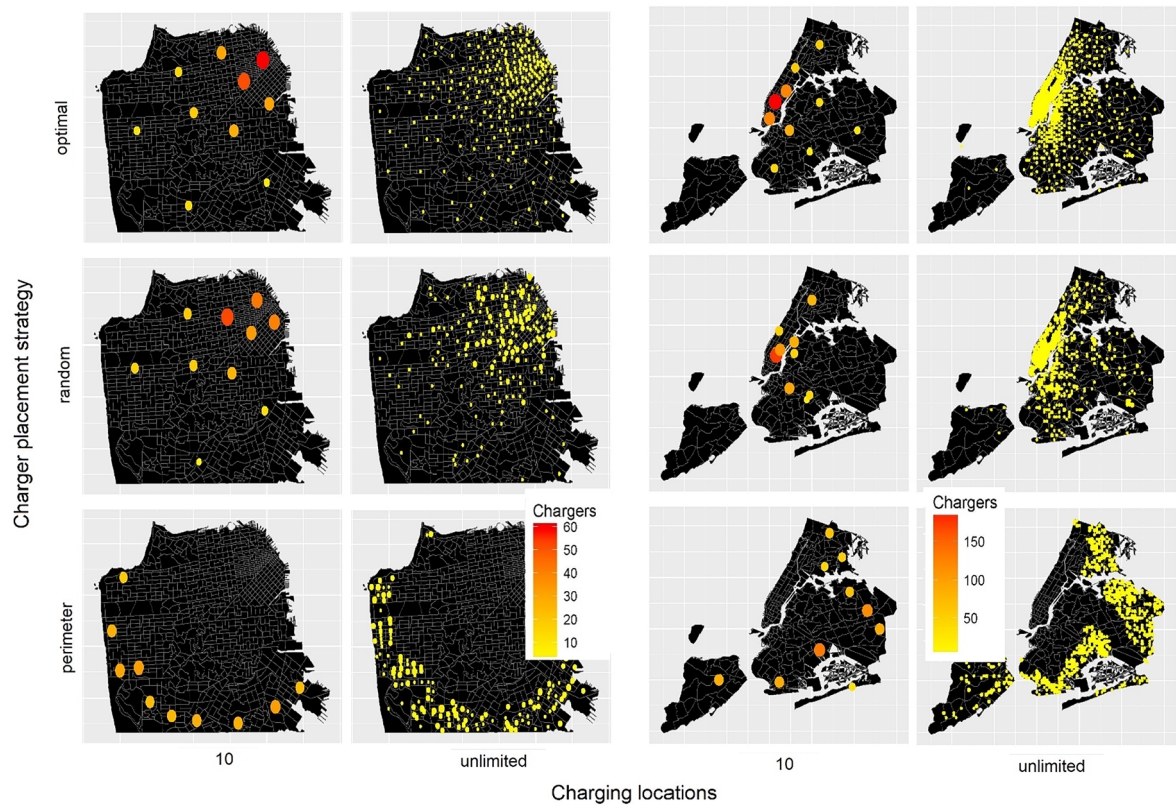
**Fig. 7.** Results for simulation runs with different strategies for charging relocation and charger placement. In “optimal” simulations, chargers were clustered based on trip origins and destinations. In “random” simulations, charger locations were selected randomly after clustering trip origins and destinations to 5000 points, and in “perimeter” and “commute” simulations, charger locations were selected randomly from points in the lowest 20% of trips per square mile. Each simulation was run with three and four 50-kW chargers per square mile for NYC and SF, respectively.

rated to at least 50 kW. We find that adding more charging infrastructure beyond this threshold does not significantly improve fleet performance, consistent with previous studies that have found diminishing returns to adding more charging infrastructure (Jia et al., 2018; Kontou et al., 2019).

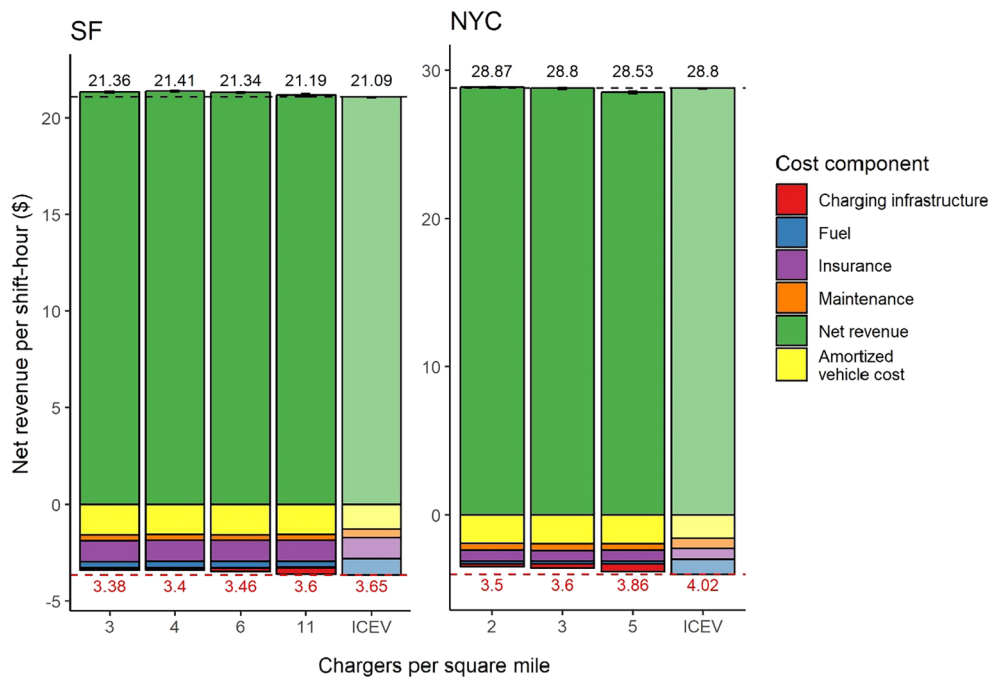
As a result of high utilization, we estimate that the cost of installing these fast chargers is quiet low: \$0.07/shift-hour in SF and \$0.17/shift-hour in NYC, including demand charges (see Table 2 for cost model details). In contrast, we estimate that all other ridesourcing BEV expenses fall in the range of \$3.27–\$3.40/shift-hour including both operating costs and amortized capital costs. The impact of BEVs on net revenue is either positive or close to zero in all scenarios (Fig. 9). In other words, even if the charging infrastructure is significantly overbuilt, resulting in only 5–10 h of utilization per day (11 and 5 chargers per square mile for SF and NYC, respectively), the cost still represents at most 2% of driver earnings and an even lower proportion of total revenue. Our sensitivity analyses show that—in every case we tested—differences in revenue between ICEV and BEV fleets fall within the range of -\$0.80 to \$0.80/shift-hour, or a few percent of total revenue (see Appendix C). This comparison assumes that fleets or their drivers pay for charging infrastructure; any public infrastructure funding will increase potential savings for ridesourcing fleets.

Charging infrastructure could be paid for with less than 1% of revenue from the rideshare tax in NYC (Lumb, 2018), or less than





**Fig. 8.** Maps of distributions of chargers in SF (left) and NYC (right) for each placement strategy and for both unlimited locations and placement restricted to 10 locations. The color and size both represent the number of chargers at each location.



**Fig. 9.** Average expenses and net revenue of operating a ridesourcing BEV per shift-hour, broken down by component for each city. Dashed lines show comparison to total ICEV cost and net revenue, while red numbers show total expenses and black numbers show net revenue after expenses. Error bars show difference between BEV scenarios (only 50-kW scenarios that provide equivalent service to ICEVs are shown). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

4% of the proposed rideshare tax in SF (Sabatini, 2018). While we do not make any claim about the specific levels of utilization required to support charger deployment, these results suggest that utilizations as low as 20% may be sufficient. Below this point, the net revenue from BEVs will decrease as charging costs per kWh increase exponentially.

## 5. Conclusion

While our analysis is focused on two cities, it yields some general implications. Our analysis suggests that ridesourcing fleets can be electrified while maintaining or potentially even increasing net revenues. The cost of charging infrastructure is a relatively small fraction of the total cost of an electric, ride-sourced trip, indicating that it might be prudent to slightly overbuild capacity to ensure high-quality service. For instance, 50-kW chargers placed at a density of roughly three to four chargers per square mile would allow the fleet to better serve demand while also increasing revenue slightly.

Efficiently routing vehicles to charge makes fleet performance insensitive to changes in vehicle range, which may enable batteries to be used much longer than currently expected, further lowering costs. Although short-range BEVs may not readily serve all of drivers' personal trips, leasing or renting vehicles for ridesourcing is already common, and almost two-thirds of ridesourcing drivers in NYC report acquiring a new vehicle for the sole purpose of working in the ridesourcing industry (Parrott and Reich, 2018).

From a policy perspective, justification for public intervention has centered on the environmental benefits of shared, electric vehicles (Bauer et al., 2018a). However, this analysis suggests that when chargers are utilized efficiently switching to BEVs could be achieved without increasing the cost of ridesourcing services. A combination of mandates on ridesourcing companies coupled with public investments in charging infrastructure can help ensure that ridesourcing companies invest in driver adoption of BEVs while freeing them of concerns related to availability and utilization of charging infrastructure. Mandates that require industry to obtain a certain percentage of miles from zero-emission vehicles would naturally spur the development of innovative financing and leasing strategies for BEVs as well as the development of efficient charging-routing algorithms. One of the first instances of such a mandate is the California Clean Miles Standard and Incentive program, which sets targets for reduction in emissions per passenger-mile for ridesourcing companies beginning in 2023 (California State Legislature, 2018). Our work is the first to suggest that such policies are not only feasible but could deliver emissions reductions at low cost.

It is important to note that our work can be extended to address the following limitations. First, we do not have data regarding actual driver behavior in between trips, so it is possible that the way we have modeled deadheading activity and charging behavior could bias our results. For example, we assume that drivers never wait at charging stations with their app turned off. In the “opportunity” and “threshold” cases, drivers will only relocate to charge when there is a charger available for the whole time they wish to charge. In the “baseline” scenario, if there are no available chargers when a driver arrives at a station, they are either routed to serve a trip or relocate to the closest charging station with available spots. Similarly, we did not have access to actual ridesourcing trip data for an entire metropolitan area in either of the cities we analyzed; in each case, data from several sources are combined to extrapolate individual trips. In both cities, these data consisted of only an average weekday, ignoring variation across days of the year. Future work could improve on this approach, especially with access to proprietary data. That said, because we modeled the ICEV and BEV fleets consistently, we expect our comparisons to be robust to inaccuracies in driver behavior. Given the difficulty of obtaining and publishing analysis of proprietary data, our approach for developing insights with limited data may prove useful in future work. Regardless, we hope this study shows the value of detailed ridesourcing data and thus encourages more data sharing in the future.

Future work should also seek to incorporate charging activity by other types of BEVs, such as private vehicles and taxis. In particular, previous studies have shown that ride-sourcing and taxis may provide complementary services (Y. Dong et al., 2018), so charging activity by electric taxis could either increase charger utilization or interfere with ridesourcing charging.

In addition, future work could incorporate dynamics of a fleet that changes over time with the introduction of both electric and automated vehicles. While in this work we focus on currently-available vehicle models to study present-day ridesourcing fleets, future technology may include a variety of different options. For example, it is likely that performance could be further improved by using a heterogeneous mix of vehicles with different battery ranges, as shown in Sheppard et al. (2019). To provide recommendations for managing gradual electrification over time, it will also be important to conduct simulations of fleets with both ICEVs and BEVs at varying levels of BEV penetration.

Finally, while we have relied on illustrative estimates for cost components, actual costs could vary greatly with location, especially for charging infrastructure. Incorporating the cost of acquiring and maintaining parking spaces for chargers, and the cost of developing and operating routing software would improve the accuracy of the levelized life cycle cost per mile for BEVs. Nevertheless, we expect that our main conclusions are unlikely to change.

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## Author contributions

Gordon S. Bauer: gathered data, conducted analysis, wrote manuscript.

Deepak Rajagopal: provided guidance and conceptual insight, assisted with writing manuscript.

Jeffery B. Greenblatt: provided guidance and conceptual insight, reviewed manuscript.

Amol Phadke: provided guidance and conceptual insight, reviewed manuscript

## Appendix A. Vehicle activity results

Figs. A1 and A2 show more details related to vehicle activity: the first shows overall averages for the amount of time devoted to each activity, while the second shows vehicle counts disaggregated by activity and minute in SF.

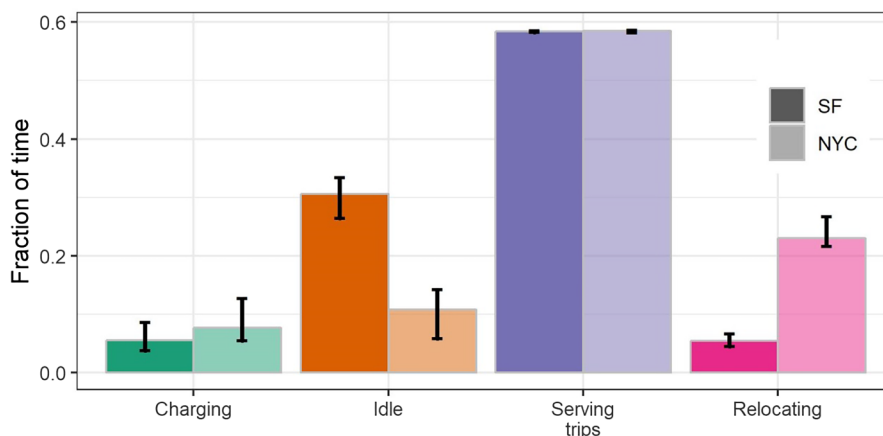


Fig. A1. Fraction of time devoted to each activity in each city for all simulations resulting in equivalent service to ICEV fleets.

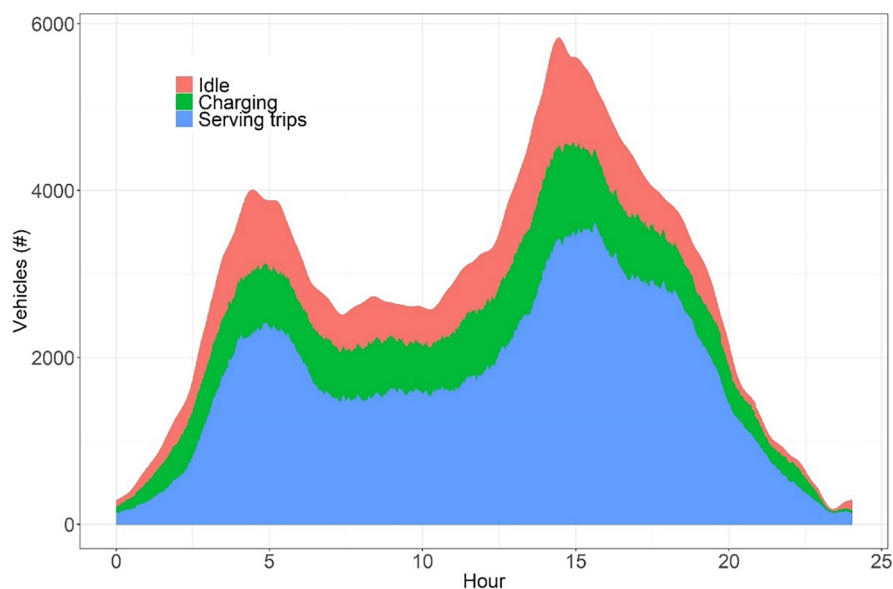


Fig. A2. Vehicle activity by time of day with 7 kW charging in San Francisco.

## Appendix B. Extended simulation results

### 1. NYC

Figs. B1–B6 show results for each city for each measure of fleet performance: demand served (and correspondingly driver revenue), average wait times, and deadheading (the ratio of empty miles to passenger miles).

### 2. San Francisco

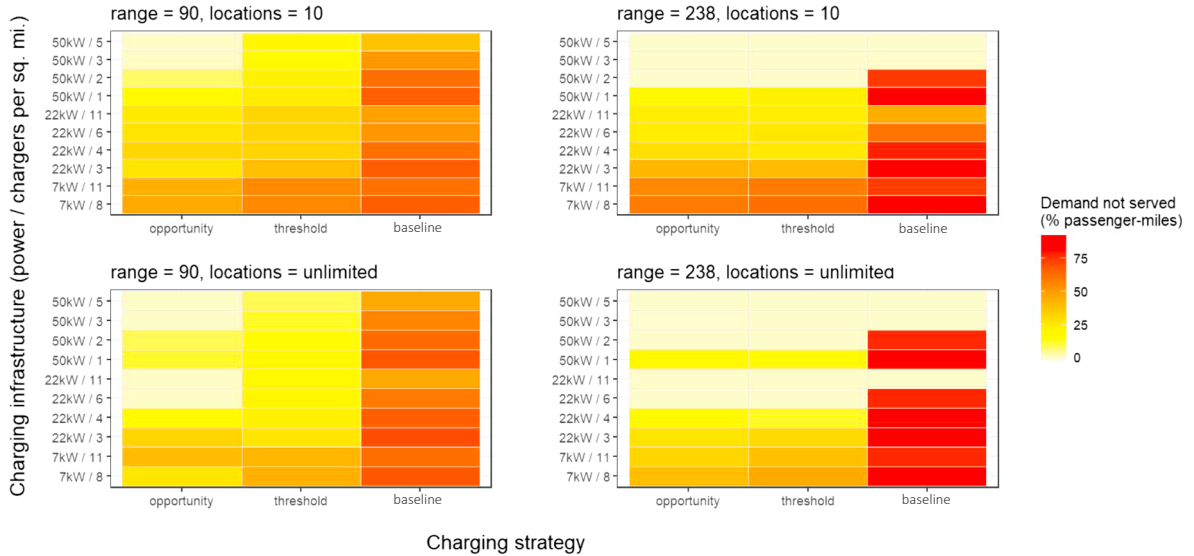


Fig. B1. Percent passenger-miles served by BEV fleets in NYC under different charging and vehicle scenarios.

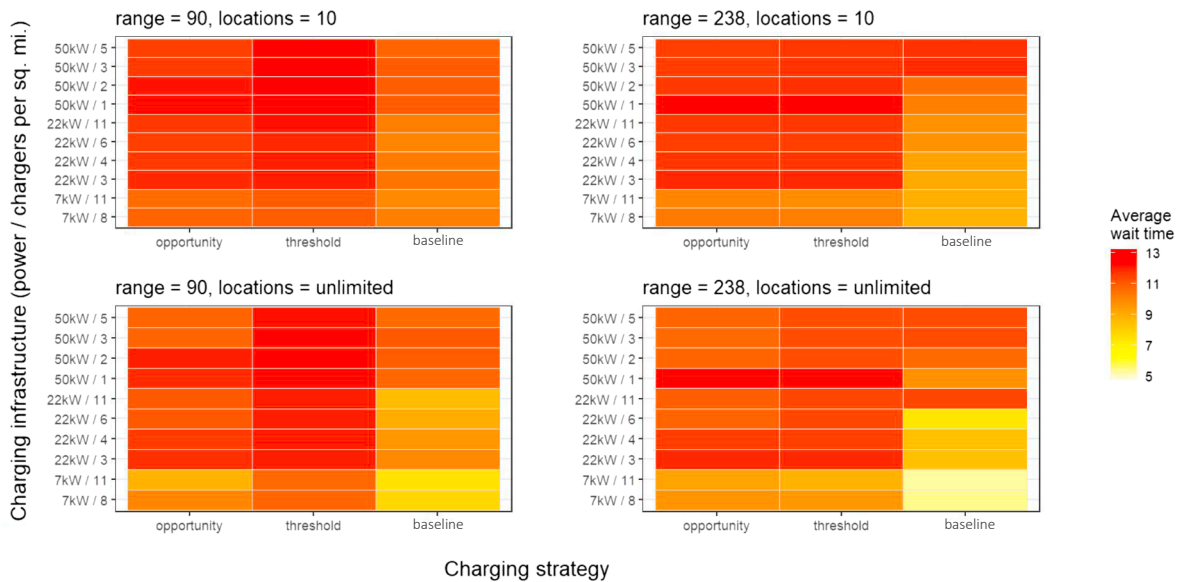


Fig. B2. Average wait times in NYC by simulation scenario.

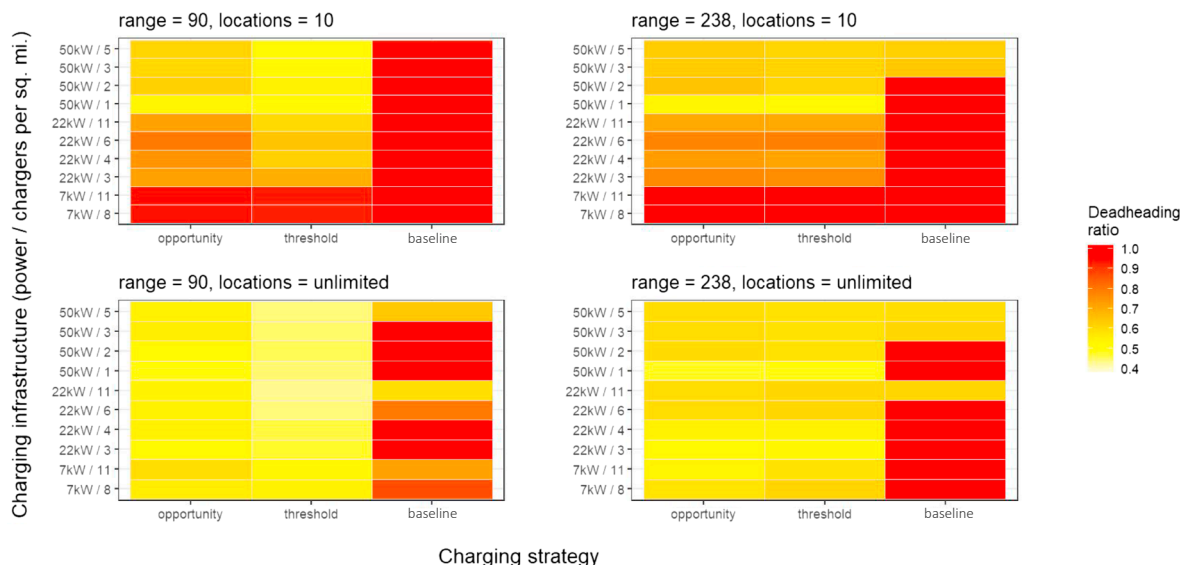


Fig. B3. Ratio of empty miles to passenger miles in NYC by simulation scenario.

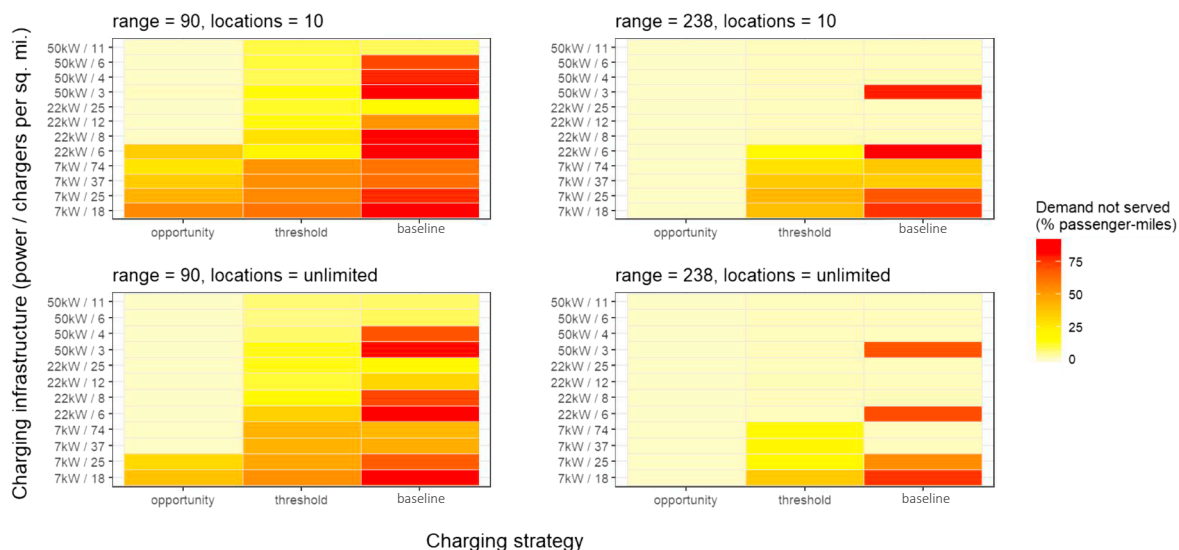


Fig. B4. Percent passenger-miles served by BEV fleets in SF under different charging and vehicle scenarios.

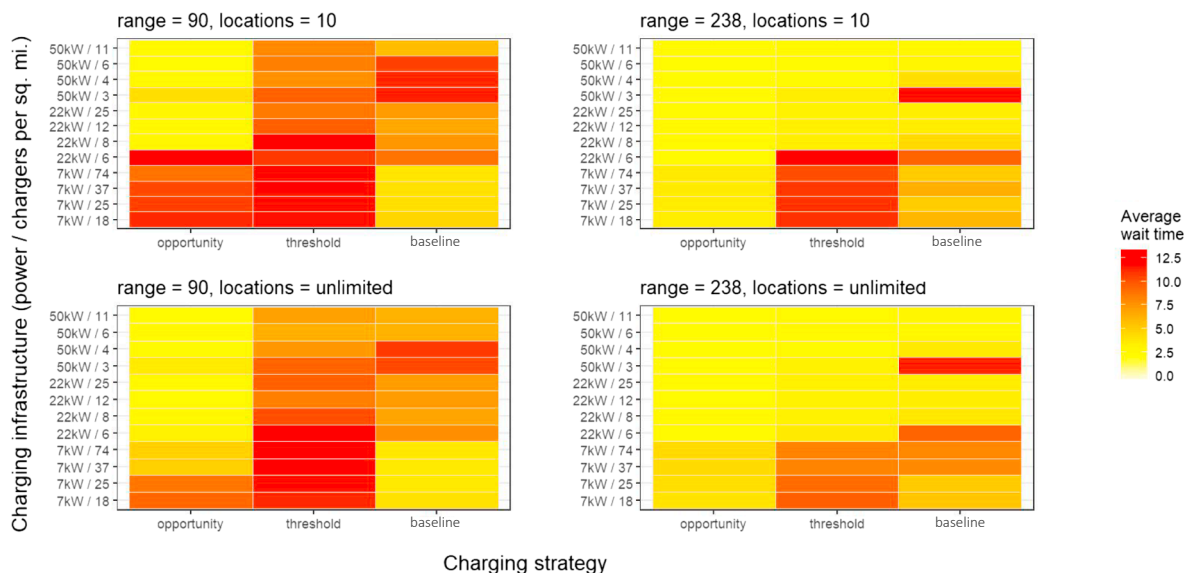


Fig. B5. Average wait times in SF by simulation scenario.

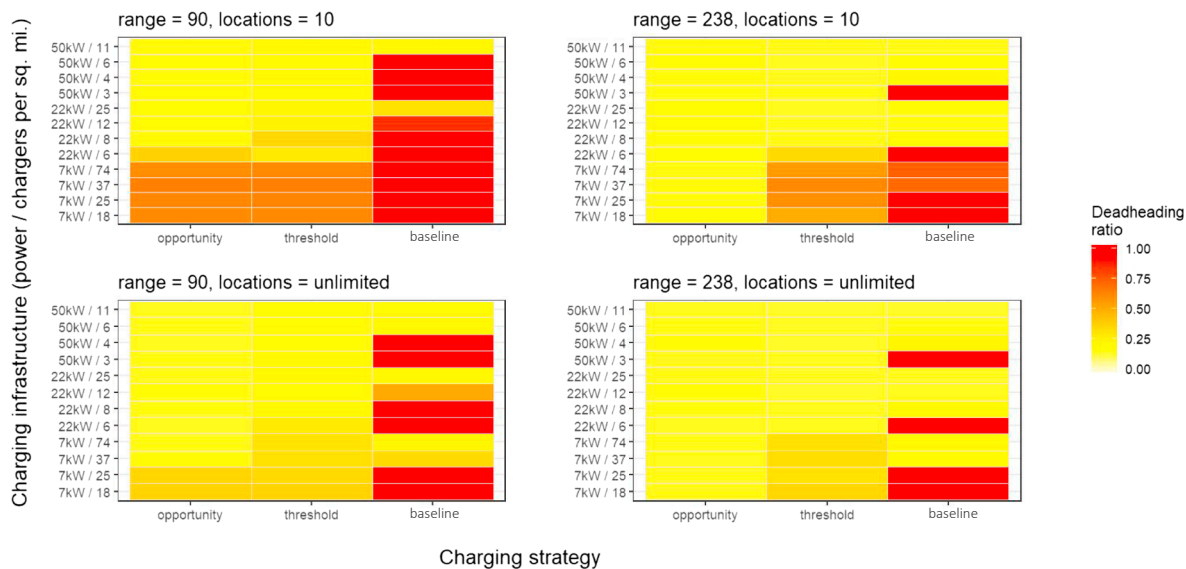


Fig. B6. Ratio of empty miles to passenger miles in SF by simulation scenario.

## Appendix C. Sensitivity analysis

Fig. C1 shows the impact of changing cost assumptions on the difference in net revenue between BEV and ICEV fleets in each city, with each scenario described in Table C1. Fig. C2 shows the impact of changing the assumption that idle vehicles rebalance in anticipation of future demand.

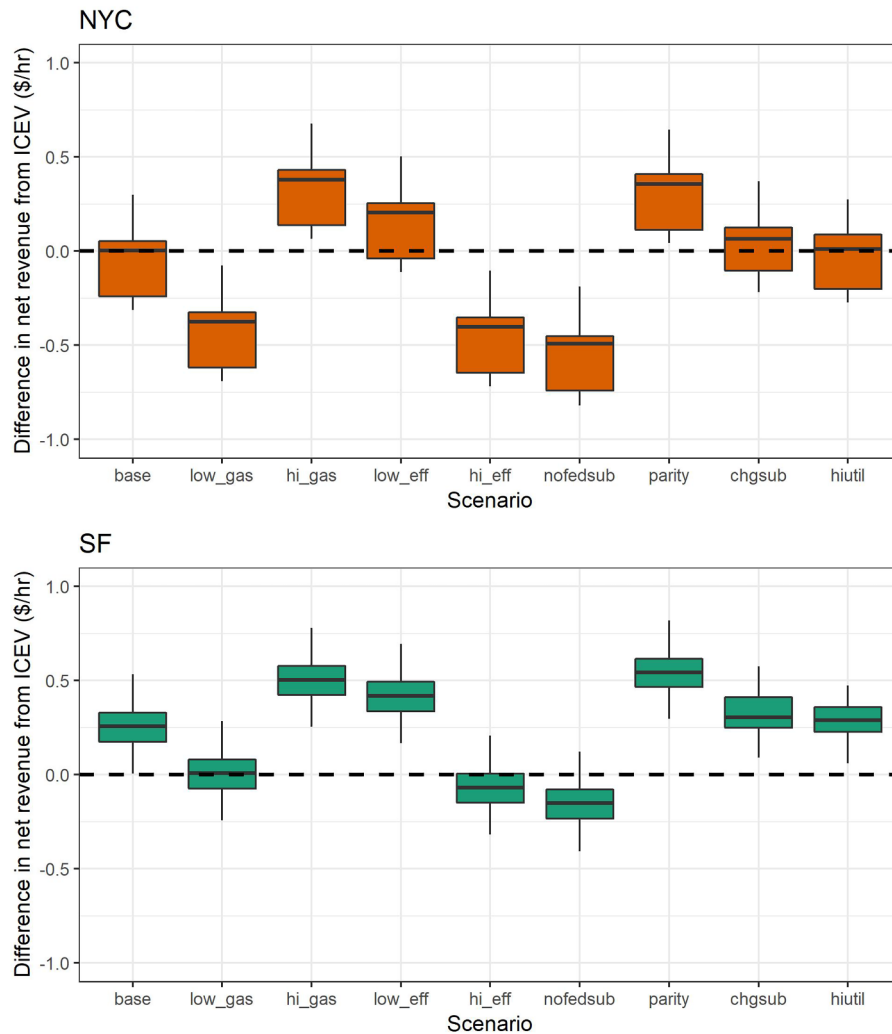


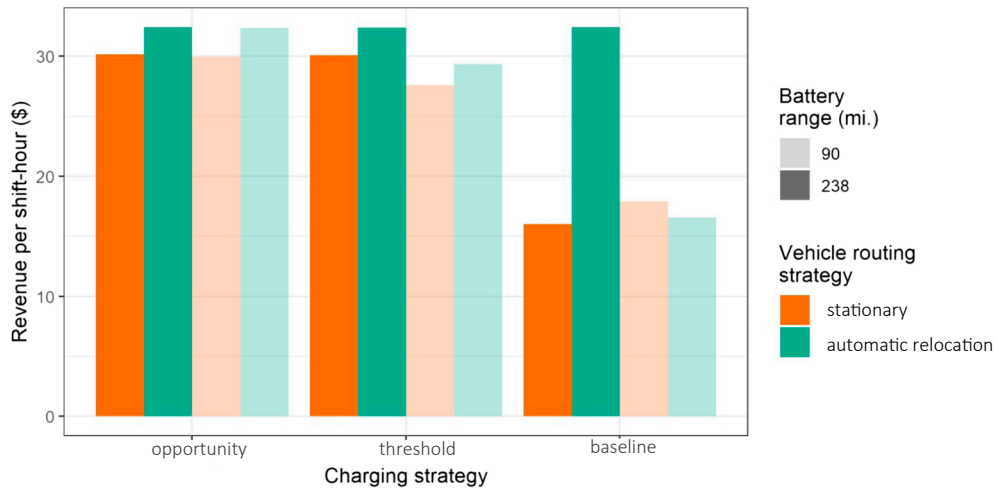
Fig. C1. Impact of changing cost assumptions on potential savings from switching to BEVs. For more details on each scenario, see Table C1.

Table C1

Description of cost model sensitivity analysis scenarios.

Scenario	Description
base	Base scenario, described in Table 2
low_gas	Gas prices decrease by \$1/gallon
hi_gas	Gas prices increase by \$1/gallon
low_eff	ICEV fuel economy = 25 miles/gallon
hi_eff	ICEV fuel economy = 50 miles/gallon
nofedsub	No federal tax subsidy for BEVs
parity	BEV 238 purchase price is the same as ICEV (\$23,845), and BEV 90 price decreases accordingly
chgsub	Cost of charging installation is ignored, assuming it is paid for through public funding
hiutil	Vehicles are used by multiple drivers, increasing vehicle utilization to 20 h per day





**Fig. C2.** Comparison of simulation results by vehicle routing strategy (“stationary” represents simulations in which vehicles never rebalance in between trips to match demand, while “automatic relocation” represents the base scenario with clairvoyant rebalancing). Results show that removing clairvoyance decreases vehicle revenue somewhat, but the impact of charging relocation strategy and battery range remain the same, with the exception of the “baseline” scenario, where longer-range BEVs can no longer serve demand.

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